International Journal of Research in Industrial Engineering

www.riejournal.com

Int. J. Res. Ind. Eng. Vol. 14, No. 1 (2025) 99–114.

Paper Type: Research Paper

Revolutionizing Municipality Performance Evaluation: A Dynamic Network Fusion of BSC and DEA

Yusof Chaharlang[1], Hamed Soleimani[1,*], Esmaeil Mehdizadeh[1], Alireza Alinejad[1]

[1] Department of Industrial Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran; chaharlang.amir@yahoo.com; hamed.soleimani1362@gmail.com; emehdi@qiau.ac.ir; alalinezhad@gmail.com.

Citation:

Received: 18 July 2024 *Revised: 20 September 2024* *Accepted: 14 October 2024*	Chaharlang, Y., Soleimani, H., Mehdizadeh, E., & Alinejad, A. (2025). Revolutionizing municipality performance evaluation: A dynamic network fusion of BSC and DEA. *International journal of research in industrial engineering, 14*(1), 99-114.

Abstract

This study introduces an advanced performance measurement system for 31 municipalities in Tehran and Shahriar, integrating the Balanced Scorecard (BSC) and Data Envelopment Analysis (DEA) methodologies. The combination of BSC and DEA was chosen because BSC offers a multidimensional framework for assessing performance from diverse perspectives, while DEA provides a quantitative tool for evaluating efficiency, particularly useful when dealing with multiple inputs and outputs. Together, they allow for both qualitative and quantitative evaluation of municipal performance, addressing the need for comprehensive performance assessment. However, traditional DEA models often fail to account for dynamic changes and intermediate linkages between these perspectives over time. The Dynamic Network Slacks-Based Model (DNSBM) of DEA, proposed in this study, addresses these limitations by incorporating both network interdependencies and dynamic changes in performance evaluation. Field studies and expert interviews revealed interconnections between BSC perspectives, and dynamic changes were modeled by linking networks over multiple periods. The model estimated efficiency values for each period, showing an average overall score of 0.857, with specific scores for financial (0.94), learning and growth (0.83), internal processes (0.96), and customer (0.34). Statistically significant correlations were found between most perspectives, except financial and learning/growth. The model identified dynamic performance trends, inefficiency levels, and strategies to improve underperforming DMUs, offering a comprehensive approach to enhancing municipal performance.

Keywords: Financial, Learning and growth, Internal business processes, Customer perspectives.

1 | Introduction

Efficiency indicators play a crucial role in aiding decisions regarding production units. One of the methods used to assess efficiency is Data Envelopment Analysis (DEA), a non-parametric technique designed to

Corresponding Author: hamed.soleimani1362@gmail.com

https://doi.org/10.22105/riej.2024.468397.1457

evaluate the efficiency of Decision-Making Units (DMUs) that utilize various inputs to generate multiple outputs [1]. Following the pioneering studies that introduced DEA and its application across various economic sectors, this methodology has continually evolved and matured. Numerous scholars have contributed their own models to the DEA literature [2–9].

To depict the production process more realistically, evaluating nonproportional projections using non-radial models becomes essential [10]. In response, Tone [11] introduced the SBM model, integrating the slacks of each input/output into a comprehensive slacks-based efficiency measure.

In the field of DEA research, there's a growing interest in understanding inefficiencies within DMUs that have complex structures. Researchers aim not only to measure overall efficiency but also to examine divisional efficiencies, all under one framework [5], [9], [10]. This focus has led to the development of network DEA methods, which are known for their ability to identify inefficiencies more precisely compared to traditional DEA models. While traditional DEA views DMUs as closed systems focusing only on known inputs and outputs [14], network DEA delves deeper, considering the internal structure of DMUs in efficiency calculations, resulting in a more detailed and insightful evaluation.

Tone and Tsutsui [15] introduced a Network DEA model that incorporates interlinked activities within a unified framework, emphasizing the significance of divisions and assessing both overall and divisional efficiency. Their proposed model considers links as continuous flows between divisions, aiming to resolve conflicts arising from the dual role of intermediate measures. The dynamic DEA model extends its scope to accommodate long-term perspectives by integrating carry-over activities. This approach allows for the measurement of period-specific efficiency while optimizing performance over extended durations. Tone and Tsutsui [16], In their study, extended their NSBM model [15] for the multi-period evaluation, naming it Dynamic SBM (DSBM).

Huang and Wang [17] developed a dynamic network DEA game cross-efficiency model to assess the efficiency of China's high-tech industries, revealing a 45% improvement potential, with R&D and commercialization efficiency showing distinct trends. Liu et al. [18] combine dynamic network DEA and cross-efficiency evaluation to assess bus transit benefits in 33 Chinese cities, finding that smaller cities outperform larger ones in service effectiveness. Anouze et al. [19] propose a dynamic network DEA framework for evaluating national innovation systems in 23 oil-producing countries, identifying Korea and Sweden as top performers while offering policies for improving efficiency in less effective countries.

Developing numerical models for performance measurement heavily relies on accurately delineating the production process. This entails effectively defining the production process and its parameters by meticulously choosing pertinent variables to represent inputs, outputs, and contextual influencers. Consequently, the inclusion of performance indicators across multiple dimensions becomes imperative for modeling and gauging the efficiency and performance of DMUs.

In this context, the Balanced Scorecard (BSC), proposed by Kaplan & Norton [20], stands out as an excellent choice for integrating indicators from diverse perspectives. Its framework allows the incorporation of multifaceted indicators across financial, customer, internal processes, and learning growth dimensions. This comprehensive approach of the BSC aligns perfectly with the need to encompass various dimensions when modeling and estimating the efficiency and performance of DMUs. By leveraging the BSC's structure, organizations can effectively capture and evaluate a broad spectrum of performance indicators, providing a more holistic view of their operations and facilitating informed decision-making [21].

The BSC is a vital tool for managing performance in organizations. It helps outline an organization's goals and plans by considering four key areas: finances, customers, internal processes, and learning and growth. Developed by BSC innovators, this method uses Key Performance Indicators (KPIs) to connect strategies with the organization's vision. These connections show how different factors impact performance through these four perspectives, revealing how the organization creates value and adapts its strategies. In the realm of performance evaluation literature, numerous researchers have extensively employed this technique across

diverse scientific fields to assess performance [22–26] integrated the Sustainability-Balanced Scorecard (SBSC) and Multiple Criteria Decision-Making (MCDM) techniques to assess airport sustainability. By applying DEMATEL and DANP methods, the authors establish key influences on airport performance and identify critical gaps between current performance and aspiration values.

The model was demonstrated with three international airports in Taiwan, revealing that airport image and social perspectives significantly influence performance. The study highlights the importance of addressing performance gaps in public transport and financial transparency. Daraio et al. [27] explored the integration of DEA and the BSC to address the challenge of assessing DMUs performance, particularly in relation to Intellectual Capital (IC) and intangible assets. Their study employs a three-level methodology, including systematic reviews, bibliometric analysis, and the analysis of grey literature. The authors provide a comprehensive survey of scientific works combining DEA, BSC, and IC, with a focus on the gender dimension. Additionally, they present an inclusive list of performance indicators, reclassified according to intellectual capital dimensions. This research offers important insights for improving DMU performance evaluation by integrating IC and gender considerations into existing models.

Hristov et al. [28] conducted a systematic literature review on the BSC in operations management (OM), identifying key performance drivers and outcome measures across BSC perspectives. Using a system dynamics approach, they map the relationships between these indicators and develop a dynamic strategy map for OM. The study provides a comprehensive view of how BSC perspectives and measures are interconnected, offering insights for both researchers and practitioners.

Municipalities play a crucial role in a country's growth and community development. In Iran, these government bodies provide essential services and promote urban efficiency, economic progress, and public welfare. With cities expanding, populations growing, and services diversifying, there's an urgent need for effective tools to measure how well municipalities are performing [24].

In the dynamic landscape of modern cities, municipalities face a myriad of evolving challenges, from demographic shifts to technological advancements. The need for dynamic performance evaluation within these administrative bodies has become imperative. Unlike static assessment models, a dynamic evaluation system enables municipalities to swiftly adapt to changing circumstances, gaining real-time insights into their operations and fostering agility in decision-making. By embracing such a system, municipalities can holistically assess their performance, pivot strategies promptly, and ensure long-term sustainability while effectively meeting the diverse and ever-changing needs of their communities.

In this article, we employ dynamic Network DEA and the BSC to evaluate municipal performance across diverse perspectives comprehensively. The dynamic Network DEA methodology allows for a real-time assessment of municipalities' efficiency, considering their interconnected activities and adapting to the ever-changing urban landscape. Simultaneously, the BSC offers a multi-dimensional evaluation framework, enabling the assessment of municipal performance from financial, customer-centric, internal process, and growth perspectives. By integrating these approaches, we aim to provide a comprehensive and nuanced understanding of municipal effectiveness, considering various facets crucial for sustainable urban development and enhanced governance.

2 | Backgrounds and Materials

In this section, we review the DNSBM proposed by Tone and Tsutsui [16].

Let's assume that the number of DMUs is denoted as n with indices j (where $j = 1, \dots, n$). Each DMU is subdivided into a certain number, k (where k = 1, ..., K)), and time periods t (where (t = 1, ..., T)). Each DMU possesses inputs and outputs in period (t) through transfer (linkage) to the subsequent period (t + 1).

Let mk and rk represent the number of inputs and outputs for each division k (div (k)), where (k, h) signifies from div (k) to div (h) and L_{hk} denotes the set of all intermediate products from div (k) to div(h).

2.1 | Inputs and Outputs Notations

$X_{ijk}^{t} \in R + (i = 1, \ldots, mk; j = 1, \ldots, n; K = 1 \ldots, K; t = 1, \ldots, T)$.

Input (i) from div(k) related to DMU(j) in period (t).

$Y_{ijk}^{t} \in R + (r = 1, \ldots, rk; j = 1, \ldots, n; K = 1 \ldots, K; t = 1, \ldots, T)$.

Output (r) from div (k) related to DMU(j) in period (t).

2.2 | Intermediate Products

$Z_{j(k,h)t}^{t} \in R + (j = 1, \ldots, n; l = 1, \ldots, L_k; K = 1 \ldots, K; t = 1, \ldots, T-1)$.

Represents the intermediate product between div (k) and div (h) in DMU (j) in period (t), where (L_{kh}) is the number of links between (k) and (h).

2.3 | Carryovers

$Z_{jkl}^{(t,t+1)} \in R + (j = 1, \ldots, n; l = 1, \ldots, L_k; K = 1 \ldots, K; t = 1, \ldots, T-1)$.

Represents the carryover activities from div (k) to div (h) in DMU (j) from period (t) to (t + 1), where (LK) is the number of carryovers from div (k).

$$\theta_o^* = \operatorname{Min} \frac{\sum_{t=1}^{T} W^t \sum_{k=1}^{K} W^k \left[1 - \frac{1}{m_k + \mathrm{linkin}_k + \mathrm{nbad}_k} \left(\sum_{i=1}^{m_k} \frac{s_{iok}^{t-}}{x_{iok}^{t}} + \sum_{(kh)_l=1}^{\mathrm{linkin}_k} \frac{s_{o(kh)_l in}^{t}}{z_{o(kh)_l in}^{t}} + \sum_{k_l=1}^{\mathrm{nbad}_k} \frac{s_{ok_l bad}^{(t,(t+1))}}{z_{ok_l bad}^{(t,(t+1))}}\right)\right]}{\sum_{t=1}^{T} W^t \sum_{k=1}^{K} W^k \left[1 + \frac{1}{r_k + \mathrm{linkout}_k + \mathrm{ngood}_k} \left(\sum_{r=1}^{r_k} \frac{s_{rok}^{t+}}{y_{rok}^{t}} + \sum_{(kh)_l=1}^{\mathrm{linkout}_k} \frac{s_{o(kh)_l out}^{t}}{z_{o(kh)_l out}^{t}} + \sum_{k_l=1}^{\mathrm{ngood}_k} \frac{s_{ok_l good}^{(t,(t+1))}}{z_{ok_l good}^{(t,(t+1))}}\right)\right]}. \quad (1)$$

$$\text{s.t.} \sum_{j=1}^{n} \lambda_{jk}^{t} x_{ijk}^{t} = x_{iok}^{t} - s_{iok}^{t-}. \quad (2)$$

$$\sum_{j=1}^{n} \lambda_{jk}^{t} y_{rjk}^{t} = y_{rok}^{t} + s_{rok}^{t+}. \quad (3)$$

$$\sum_{j=1}^{n} \lambda_{jk}^{t} z_{j(kh)_{free}}^{t} = \sum_{j=1}^{n} \lambda_{jh}^{t} z_{j(kh)_{free}}^{t}. \quad (4)$$

$$\sum_{j=1}^{n} \lambda_{jk}^{t} z_{j(kh)_{fix}}^{t} = \sum_{j=1}^{n} \lambda_{jh}^{t} z_{j(kh)_{fix}}^{t}. \quad (5)$$

$$\sum_{j=1}^{n} \lambda_{jk}^{t} z_{j(kh)_{fix}}^{t} = z_{o(kh)_{fix}}^{t}. \quad (6)$$

$$\sum_{j=1}^{n} \lambda_{jh}^{t} z_{j(kh)_{fix}}^{t} = z_{o(kh)_{fix}}^{t}. \quad (7)$$

$$\sum_{j=1}^{n} \lambda_{jh}^{t} z_{j(kh)_{in}}^{t} = z_{o(kh)_l in}^{t} - s_{o(kh)_l in}^{t}. \quad (8)$$

$$\sum_{j=1}^{n} \lambda_{jk}^{t} z_{j(kh)_{in}}^{t} = z_{o(kh)_l out}^{t} + s_{o(kh)_l in}^{t}. \quad (9)$$

$$\sum_{j=1}^{n} \lambda_{jk}^{t} z_{jk_l\alpha}^{(t,(t+1))} = \sum_{j=1}^{n} \lambda_{jk}^{t+1} z_{jk_l\alpha}^{(t,(t+1))}. \quad (10)$$

$$\sum_{j=1}^{n} \lambda_{jk}^{t} z_{jk_l good}^{(t,(t+1))} = z_{ok_l good}^{(t,(t+1))} + s_{ok_l good}^{(t,(t+1))}. \quad (11)$$

$$\sum_{j=1}^{n} \lambda_{jk}^{t} z_{jk_l bad}^{(t,(t+1))} = z_{ok_l bad}^{(t,(t+1))} - s_{ok_l bad}^{(t,(t+1))}. \quad (12)$$

$$\sum_{j=1}^{n} \lambda_{jk}^{t} = 1. \quad (13)$$

$$s_{ok_l bad}^{(t,(t+1))} \geq 0, s_{ok_l good}^{(t,(t+1))} \geq 0, \lambda_{jk}^{t} \geq 0, s_{rok}^{t+} \geq 0, s_{o(kh)_l in}^{t} \geq 0, s_{iok}^{t-} \geq 0 \text{ for all t, for all k, for all (kh), for all r, for all i.} \quad (14)$$

Based on the previous explanations regarding Network Slacks-Based Measure (NSBM) data analysis, the Dynamic Network Slacks-Based Measure (DNSBM) model is formulated as *Eqs. (1)-(14)*:

The *Constraint (13)* ensures Variable Returns To Scale (VRS) assumption of production, and its removal transforms the problem to constant returns to scale. (W^t) and (W^k) represent the importance weights associated with each period and subunit, respectively, determined by the decision-maker exogenously.

$$\tau_o^{t^*} = \text{Min} \frac{\sum_{k=1}^{K} W^k \left[1 - \frac{1}{m_k + linkin_k + nbad_k} \left(\sum_{i=1}^{m_k} \frac{s_{iok}^{t-}}{x_{iok}^{t}} + \sum_{(kh)_l=1}^{linkin_k} \frac{s_{o(kh)_l in}^{t}}{z_{o(kh)_l in}^{t}} + \sum_{k_l=1}^{nbad_k} \frac{s_{ok_l bad}^{(t,(t+1))}}{z_{ok_l bad}^{(t,(t+1))}}\right)\right]}{\sum_{k=1}^{K} W^k \left[1 + \frac{1}{r_k + linkout_k + ngood_k} \left(\sum_{r=1}^{r_k} \frac{s_{rok}^{t+}}{y_{rok}^{t}} + \sum_{(kh)_l=1}^{linkout_k} \frac{s_{o(kh)_l out}^{t}}{z_{o(kh)_l out}^{t}} + \sum_{k_l=1}^{ngood_k} \frac{s_{ok_l good}^{(t,(t+1))}}{z_{ok_l good}^{(t,(t+1))}}\right)\right]}. \quad (15)$$

$$\delta_{ok}^{*} = \text{Min} \frac{\sum_{t=1}^{T} W^t \left[1 - \frac{1}{m_k + linkin_k + nbad_k} \left(\sum_{i=1}^{m_k} \frac{s_{iok}^{t-}}{x_{iok}^{t}} + \sum_{(kh)_l=1}^{linkin_k} \frac{s_{o(kh)_l in}^{t}}{z_{o(kh)_l in}^{t}} + \sum_{k_l=1}^{nbad_k} \frac{s_{ok_l bad}^{(t,(t+1))}}{z_{ok_l bad}^{(t,(t+1))}}\right)\right]}{\sum_{t=1}^{T} W^t \left[1 + \frac{1}{r_k + linkout_k + ngood_k} \left(\sum_{r=1}^{r_k} \frac{s_{rok}^{t+}}{y_{rok}^{t}} + \sum_{(kh)_l=1}^{linkout_k} \frac{s_{o(kh)_l out}^{t}}{z_{o(kh)_l out}^{t}} + \sum_{k_l=1}^{ngood_k} \frac{s_{ok_l good}^{(t,(t+1))}}{z_{ok_l good}^{(t,(t+1))}}\right)\right]}. \quad (16)$$

$$\rho_{ok}^{t*} = \text{Min} \frac{1 - \frac{1}{m_k + linkin_k + nbad_k} \left(\sum_{i=1}^{m_k} \frac{s_{iok}^{t-}}{x_{iok}^{t}} + \sum_{(kh)_l=1}^{linkin_k} \frac{s_{o(kh)_l in}^{t}}{z_{o(kh)_l in}^{t}} + \sum_{k_l=1}^{nbad_k} \frac{s_{ok_l bad}^{(t,(t+1))}}{z_{ok_l bad}^{(t,(t+1))}}\right)}{1 + \frac{1}{r_k + linkout_k + ngood_k} \left(\sum_{r=1}^{r_k} \frac{s_{rok}^{t+}}{y_{rok}^{t}} + \sum_{(kh)_l=1}^{linkout_k} \frac{s_{o(kh)_l out}^{t}}{z_{o(kh)_l out}^{t}} + \sum_{k_l=1}^{ngood_k} \frac{s_{ok_l good}^{(t,(t+1))}}{z_{ok_l good}^{(t,(t+1))}}\right)}. \quad (17)$$

2.4 | Period, Divisional and Period-Divisional Efficiencies

Replacing the optimal values obtained from the solution of the model into the *Eqs. (15)-(17)*, respectively, results in the Period, divisional and period-divisional Efficiencies of the DMU under consideration.

3 | Dynamic Network Structure of Municipalities

After reviewing the literature and consulting with experts, the delineation of inputs and outputs in the dynamic network structure of municipalities emerges. These elements encompass not only traditional inputs and

outputs but also intermediate products, shaping a comprehensive perspective on municipal operations and interconnections.

Inputs, outputs, carryovers, and intermediate products are presented in *Table 1*.

Table 1. Inputs, outputs, carryovers, and intermediate products and their descriptions.

Criteria and Role	Description
Input to the learning and growth perspective	The number of educated and specialized individuals employed by the municipality
Input to the learning and growth perspective	The amount of in-service training provided by the municipality per person per day.
Output from the learning and growth perspective	Employee job satisfaction level.
Intermediate Product from the Learning and growth perspective to the internal business process perspective	Employee skill level in job tasks.
Input to the internal business process perspective	The extent of outsourcing to the private sector.
Intermediate product from the internal business process perspective to the customer perspective	The production level of city development maps.
Input to the customer perspective	Citizen involvement in renovating deteriorated urban areas.
Input to the customer perspective	Attracting financial resources from domestic and international investors.
Output from the customer perspective	Growth in per capita green spaces.
Intermediate product from the customer perspective to the financial perspective	Growth in tourism services
Input to the financial perspective	Budget for municipal technical and implementation projects
Output from the financial perspective	Growth in revenues and other collectible incomes.
Output from the financial perspective	The amount of income and revenue generated from urban operations and services.
The amount of transitional budget from period t to period t+1.	Refers to the budgetary transition or changes occurring from one specific period, denoted as 't,' to the subsequent period, denoted as 't+1. It denotes the alterations, shifts, or allocations in budgetary figures, plans, or resources between two consecutive time frames.
Carryover of learning and growth perspective: employee perception of learning opportunities.	This indicator is measured with a single question: How satisfied are you with the municipal educational environment? Responses range from 1 (very satisfied) to 7 (never satisfied). The 7-point Likert scale was converted to a 100-point scale.
Carryover of internal process perspective the percentage reduction in internal process costs.	The reduction in costs related to internal operational workflows within an organization over a defined time span.
Carryover of customer perspective: Citizens' satisfaction level with services	This indicator is measured using a single question: Do you believe that the municipal government of your city or region fulfills its duties regarding customer service? Responses range from 1 (very satisfied) to 7 (never satisfied). The 7-point Likert scale was converted to a 100-point scale.

The utilization of inputs, outputs, carryovers, and intermediate products elucidates the following dynamic network structure presented in *Fig. 1*.

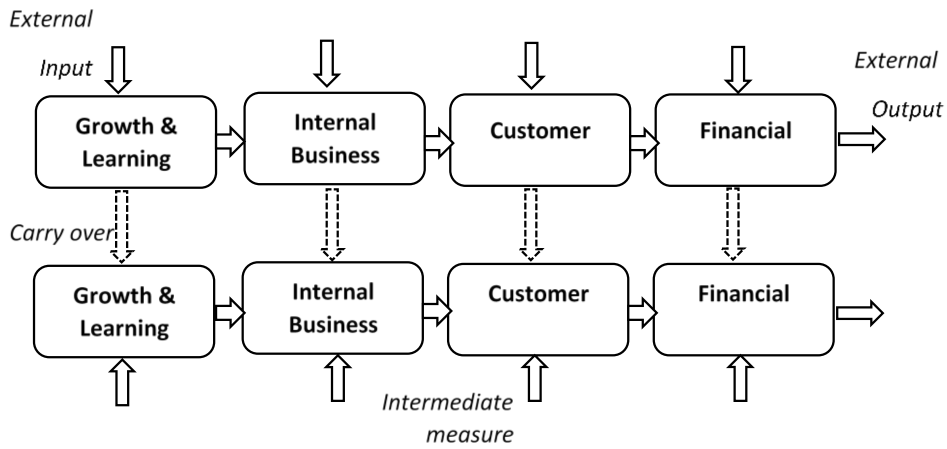

Fig. 1. The dynamic network structure of BSC.

4 | Performance Evaluation

4.1 | Divisional Efficiency (Efficiency from Different Perspectives of the BSC)

One of the advantages of the DNSBM model is that it provides the ability to separately observe performance scores for the perspectives of the BSC model in each year of the observed periods. By implementing the dynamic DEA model based on the indicators presented in chapter three, the results related to the descriptive statistics of the efficiency values for different perspectives in each period, as well as the overall efficiency in each period, are presented in *Table 2*.

Table 2. Descriptive statistics of efficiency values for periods and perspectives.

	N	Minimum	Maximum	Mean	Std. Deviation
BSC99	31	0.64	1.00	0.8471	0.09846
BSC1400	31	0.68	1.00	0.8748	0.09678
BSC1401	31	0.64	1.00	0.8484	0.10526
BSC	31	0.65	1.00	0.8568	0.09116
Fin99	31	0.82	1.00	0.9458	0.05726
Fin1400	31	0.79	1.00	0.9561	0.05264
Fin1401	31	0.80	1.00	0.9303	0.06839
Fin	31	0.84	1.00	0.9441	0.05206
Learn99	31	0.42	1.00	0.8026	0.22283
Learn1400	31	0.48	1.00	0.8494	0.19394
Learn1401	31	0.38	1.00	0.8426	0.21561
Learn	31	0.47	1.00	0.8315	0.18526
Internal99	31	0.83	1.00	0.9548	0.05784
Internal1400	31	0.82	1.00	0.9655	0.05458
Internal1401	31	0.82	1.00	0.9600	0.05556
Internal	31	0.84	1.00	0.9601	0.05070
Cusomer99	31	0.31	1.00	0.6897	0.27286
Customer1400	31	0.33	1.00	0.7265	0.26312
Customer1401	31	0.28	1.00	0.6597	0.27962
Customer	31	0.34	1.00	0.6919	0.23649
Valid N (listwise)	31				

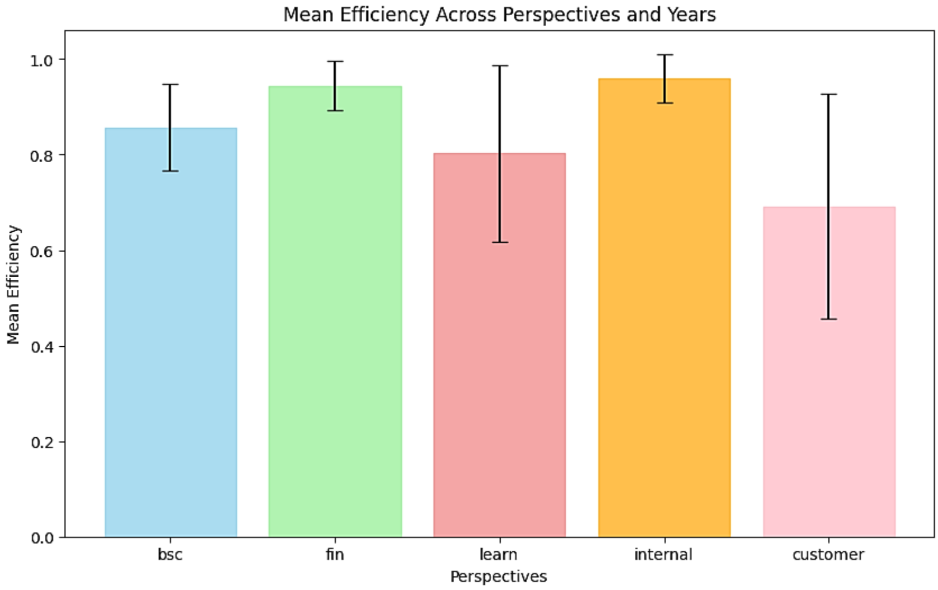

Fig. 2. Visual comparison of the mean efficiency values across different perspectives.

Fig. 2 allows for a visual comparison of the mean efficiency values across different perspectives and years, highlighting any variations or trends in performance.

Fig. 3 depicts dynamic changes in overall performance scores for four perspectives of the BSC annually from 1399 to 1401. A similar dynamic change pattern was observed, indicating a slight increase in scores from 1399 to 1400, followed by a decrease from 1400 to 1401. In general, it can be acknowledged that the average annual performance of the BSC model between 1399 and 1401 has fluctuated, namely being 0.85 in 1399, 0.87 in 1400, and again 0.85 in 1401.

The financial perspective scores were 0.95 in 1399, 0.96 in 1400, and 0.93 in 1401. The growth and learning perspective scored 0.80 in 1399, 0.85 in 1400, and 0.84 in 1401. From the internal processes perspective, the efficiency scores were 0.97 in 1399, 0.96 in 1400, and 0.96 in 1401. The customer perspective efficiency scores were 0.69 in 1399, 0.73 in 1400, and 0.66 in 1401.

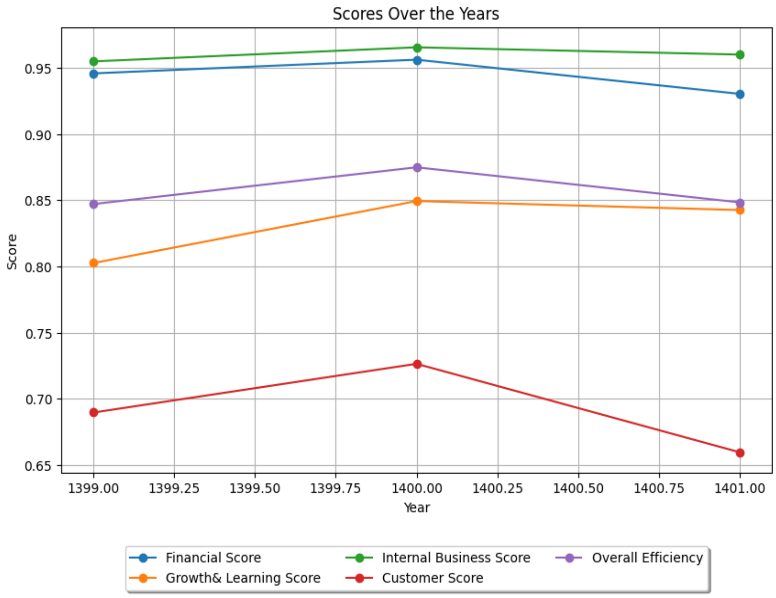

Fig. 3. Dynamic changes trend for perspective efficiency.

4.2 | Period–Divisional Efficiencies

Table 3 displays the efficiency scores obtained for 31 DMUs. The overall performance score of the BSC model over the entire observation period was 0.857 (refer to *Table 2*). The range varied from 0.651 for DMU31 to 1.000 for DMU1 and DMU2. The standard deviation of the efficiency scores was small (SD = 0.091). Twenty-four DMUs out of 31 achieved scores higher than 80%. In contrast, seven DMUs with efficiency scores below 80% had poor performance (DMU25 (0.792), DMU26 (0.771), DMU27 (0.767), DMU28 (0.761), DMU29 (0.726), DMU30 (0.703), and DMU31 (0.651)).

Table 3 also presents the period-perspective performance scores for each of the 31 DMUs. The overall performance scores for the four perspectives over the entire observation period are depicted in a line chart (*Fig. 4*) to facilitate the visualization of variations in scores obtained in each of the BSC models. The overall performance score for the financial perspective was 0.94, ranging from 0.84 (DMU25) to 1.00 (DMU1, DMU2, DMU3, DMU7, DMU11, DMU12, DMU22, and DMU28). The standard deviation of the efficiency scores was small (0.05), indicating proximity to the average efficiency values of the respective perspective.

The overall performance score from the learning and growth perspective ranged from 0.47 (DMU31) to 1.00 (DMU1, DMU2, DMU3, DMU4, DMU5, DMU6, DMU7, DMU8, DMU11, DMU13, DMU20, DMU22, and DMU25). The standard deviation was relatively large (0.18), indicating that they deviate significantly from the average efficiency values of the corresponding perspective.

The overall performance score from the internal business process perspective was 0.96, ranging from 0.84 (DMU31) to 1.00 (e.g., DMU1, DMU2, DMU3, DMU4, DMU5, DMU8, DMU9, DMU10). The standard deviation was relatively small (0.05).

The overall performance score from the customer perspective was 0.69, ranging from 0.34 (DMU22) to 1.00 (DMU1, DMU2, DMU5, DMU6, and DMU9). The standard deviation was relatively large (0.24).

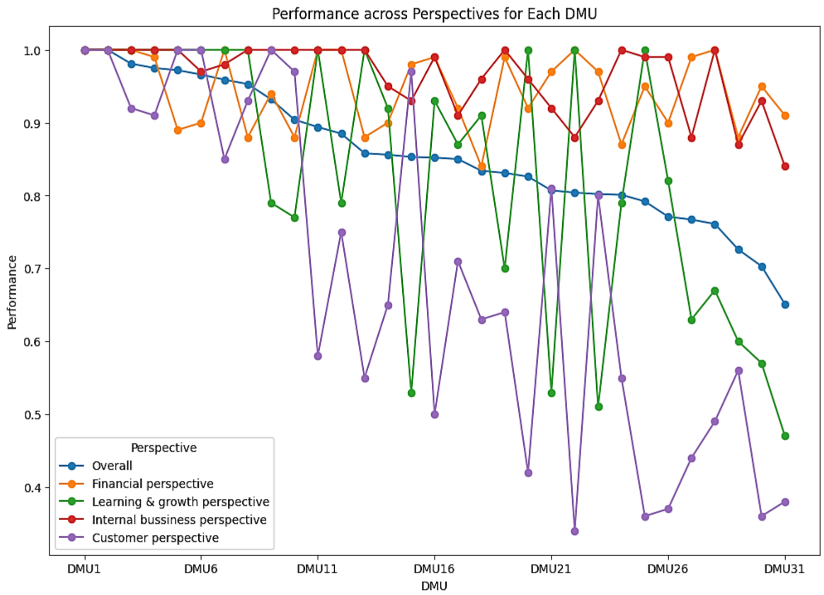

Fig. 4. Comparisons of scores.

As can be seen in *Fig. 4*, the customer perspective, compared to the other three perspectives of the BSC model, provides relatively low-performance scores. Only five DMUs (DMU1, DMU2, DMU5, DMU6, and DMU9) have been considered consistently efficient throughout the entire period. Nine DMUs out of 31 evaluated DMUs have consistently obtained performance scores lower than the average performance score (0.69) observed for the entire period. Moreover, the dynamic pattern of changes in the average performance scores annually between the years 1399 and 1401 in this perspective was equally significant and relatively large (refer to *Fig. 3* above).

4.3 | Calculating the Level of Correlation Between the Performance Values Among Various Perspectives of BSC

A set of Spearman rank correlation analyses was conducted to statistically examine the relationships between ranks (or performance scores) obtained from different DEA models. The Spearman rank correlation coefficient, a non-parametric measure of rank correlation, assesses the statistical dependence between the rankings of two models. The correlation coefficient indicates the strength and direction of the relationship between the two models and ranges from -1 (negative direction) to +1 (positive direction). This test is useful when Pearson correlation is not applicable due to the violation of normality or when ordinal variables such as rank variables are used.

Table 4 presents the results of rank correlations among the four performance perspectives of the BSC model. The rankings determined by overall performance scores over the entire observation period were used for rank correlation analysis. It is expected that not only is there a continuous correlation between two perspectives (e.g., learning-financial, learning-business, business-customer) but also a meaningful relationship exists between the overall BSC model and its four perspectives because the integrated BSC-DEA model is built on the assumption of causal relationships from the financial perspective to the customer perspective.

The results indicate that there is a statistically significant rank correlation between most models. However, there was no rank correlation between the BSC model and the financial perspective, and it was not statistically significant. Also, there was no statistically significant rank correlation between the financial perspective and the learning and growth perspective (p-value=0.243 > 0.05). *Fig. 5* displays the heatmap of correlations between the perspectives of the BSC.

Table 4. The Spearman rank correlation coefficient between the averages of the performance scores of the BSC and its perspectives.

		BSC	Fin	Learn99	Internal	Cusomer
Spearman's rho	BSC99	1.000				
	fin99	.218	1.000			
	learn99	.669	.157	1.000		
	internal99	.658		.389	1.000	
	cusomer99	.763			.461	1.000

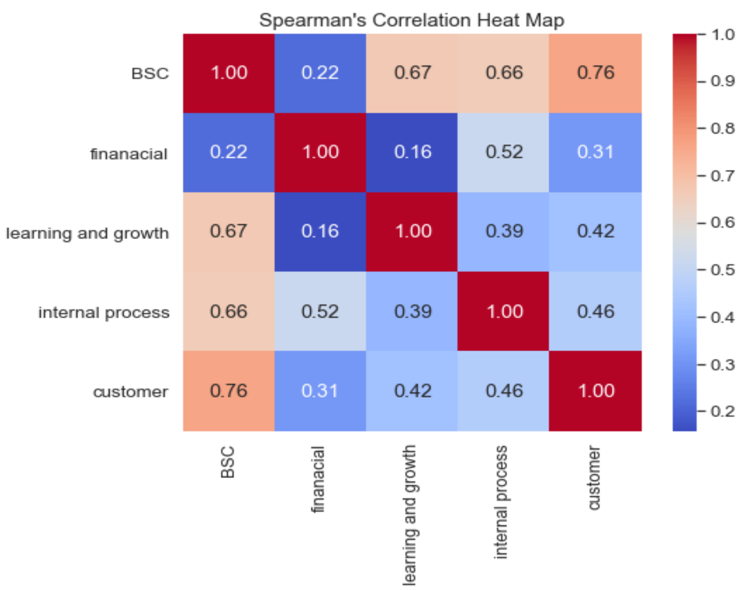

Fig. 5. The heat map of the Spearman rank correlation coefficient between the averages of the performance scores of the BSC and its perspectives.

Tables 5-7 present the results of Spearman rank correlation coefficients between the four perspectives of the BSC model for each year of the observed periods. The rankings determined by the annual average performance scores for the years 1399, 1400, and 1401 were used for a series of Spearman rank correlation analyses. The results indicate that, for the years 1399, 1400, and 1401, there are statistically significant rank correlations between most models. However, for the year 1399, no statistically significant correlations were found between the BSC model and the financial perspective, as well as between the financial perspective and the learning and growth perspective. *Fig. 6* displays the heat map of the Spearman rank correlation coefficient among the performance of perspectives in the year 1399.

Table 5. Spearman rank correlation coefficients in the year 1399.

		BSC99	Fin99	Learn99	Internal99	Cusomer99
Spearman's RHO	BSC99	1.000				
	fin99	.051	1.000			
	learn99	.689	.177	1.000		
	internal99	.534		.346	1.000	
	cusomer99	.763			.361	1.000

Correlation is significant at the 0.01 level (2-tailed).
Correlation is significant at the 0.05 level (2-tailed).
Correlation is significant at the 0.١ level (2-tailed).

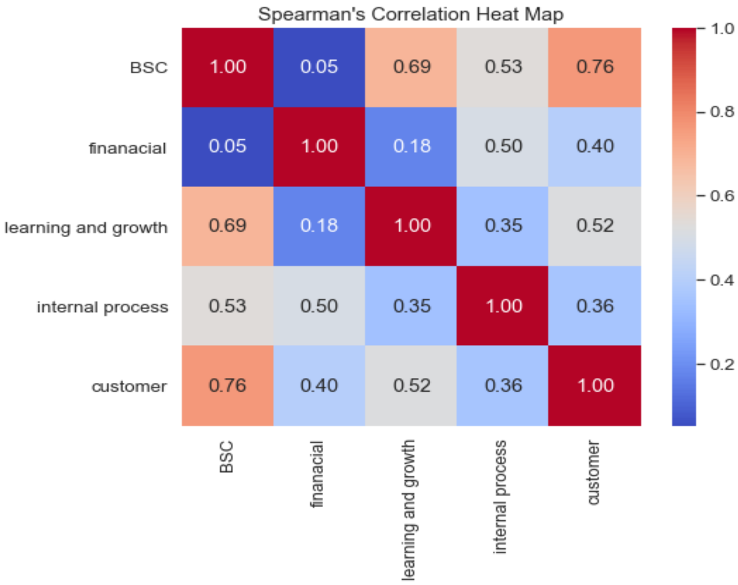

Fig. 6. The heat map of the Spearman rank correlation coefficients in the year 1399.

Fig. 6 displays the heat map of the Spearman rank correlation coefficient between the performance of the BSC and its perspectives in the year 1399. For the years 1400 and 1401, there were no statistically significant rank correlations between the financial and learning perspectives.

An unexpected result is that the ranking of the 31 DMUs from the financial perspective is not consistent with the rankings related to the learning and growth perspective, as it is assumed that they are linked by the assumed causal relationships in the BSC literature. However, it should be noted that a strong correlation does not necessarily imply a causal relationship. *Figs. 7* and *8* respectively depict the heat maps of correlations among perspectives for the years 1400 and 1401.

Table 6. Spearman rank correlation coefficients in the year 1400.

		BSC1400	Fin1400	Learn1400	Internal1400	Customer1400
Spearman's RHO	BSC1400	1.000				
	fin1400	.354	1.000			
	Learn1400	.607	.0857	1.000		
	Internal1400	.680		.356	1.000	
	Cusomer1400	.885			.523	1.000

Correlation is significant at the 0.01 level (2-tailed).
Correlation is significant at the 0.05 level (2-tailed).
Correlation is significant at the 0.1 level (2-tailed).

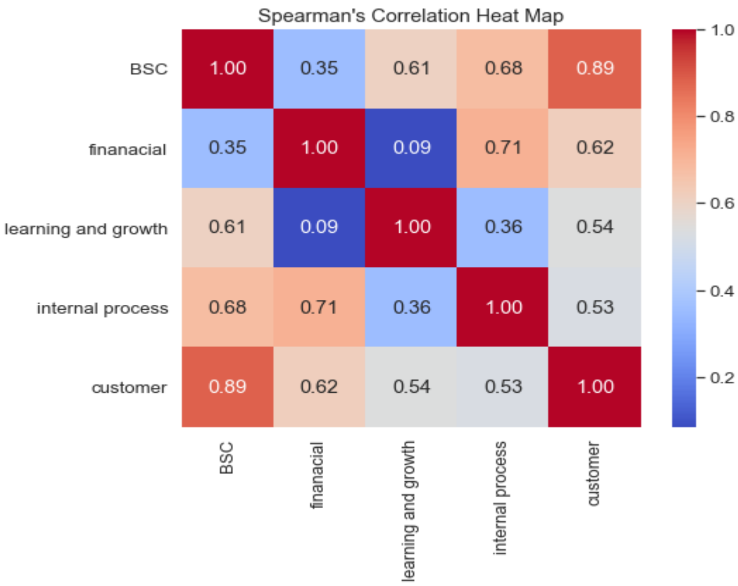

Fig. 7. The heat map of the Spearman rank correlation coefficients in the year 1400.

Fig. 7 the heat map of the Spearman rank correlation coefficients between the performance of the BSC and its perspectives in the year 1400.

Table 7 presents the Spearman rank correlation coefficients between the performance of the BSC and its perspectives in the year 1401

Table 7. Spearman rank correlation coefficients in the year 1401.

		BSC1401	Fin1401	Learn1401	Internal1401	Customer1401
Spearman's RHO	BSC1400	1.000				
	fin1400	0.324	1.000			
	Learn1400	0.628	0.1923	1.000		
	Internal1400	0.639		0.328	1.000	
	Cusomer1400	0.851			0.491	1.000

Correlation is significant at the 0.01 level (2-tailed).
Correlation is significant at the 0.05 level (2-tailed).
Correlation is significant at the 0.1 level (2-tailed).

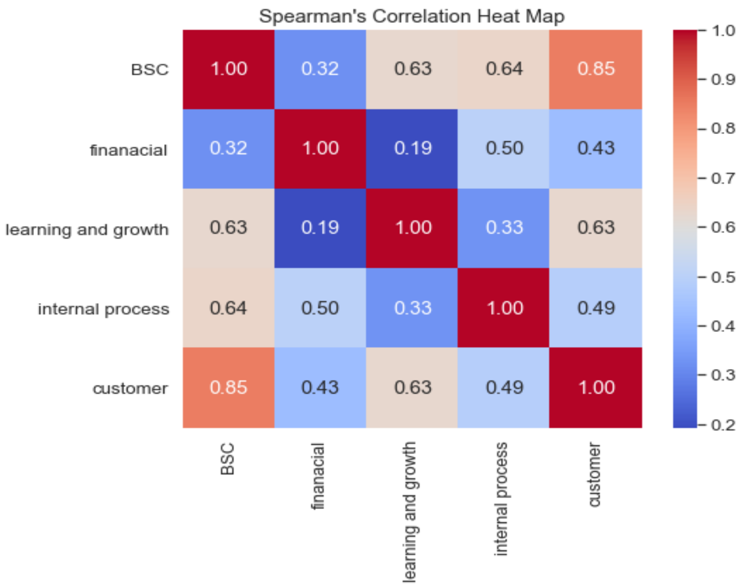

Fig. 8. The heat map of the Spearman rank correlation coefficients in the year 1401.

Fig. 8 the heat map of the Spearman rank correlation coefficients between the performance of the BSC and its perspectives in the year 1401.

5 | Conclusion

This study presents an advanced performance measurement system for 31 municipalities in Tehran and Shahriar, combining the BSC and DEA approaches. While the BSC establishes a comprehensive theoretical framework for performance measurement across multiple perspectives—financial, learning and growth, internal business processes, and customer—the Dynamic Network Slacks-Based Model (DNSBM) of DEA offers robust analytical tools to test this theoretical framework.

By utilizing a network structure to interlink BSC perspectives, the study provides a holistic view of the interconnections between various dimensions of municipal performance, supported by field studies and expert interviews. In addition to these theoretical contributions, the study captures dynamic structural changes, linking single-period networks over multiple periods to create a combined dynamic network model. This model assesses overall performance across different periods and perspectives, offering actionable strategies for improving the efficiency of underperforming DMUs by identifying inefficiency sources and providing optimized input-output values.

5.1 | Findings

The empirical analysis reveals an average overall efficiency score of 0.857, ranging from 0.651 (the lowest ranking DMU4) to 1.00 (the highest ranking DMU1 and DMU10). The financial perspective scored an average of 0.94, with eight DMUs achieving full efficiency (1.00) and DMU25 as the lowest at 0.84. The learning and growth perspective showed a more varied efficiency, with an average score of 0.83, where DMU4 ranked the lowest (0.47), and thirteen DMUs achieved full efficiency. The internal business process perspective demonstrated strong performance with an average score of 0.96, while the customer perspective had the lowest overall average at 0.34, with DMU29 scoring the lowest and five DMUs achieving full efficiency.

Spearman's test indicated statistically significant rank correlations among the BSC perspectives, except between the financial and learning/growth perspectives. This suggests that improvements in customer-related efficiency may significantly impact overall performance while learning and growth require separate attention.

5.2 | Dynamic Changes

The DNSBM-DEA model further highlights dynamic changes across BSC networks, revealing that the annual performance average increased from 1399 to 1400, followed by a decrease from 1400 to 1401. This dynamic analysis underscores the importance of continuous monitoring and adaptation to sustain efficiency improvements over time.

Additionally, the model provides a pathway for inefficient DMUs to improve by identifying specific inefficiency sources and prescribing practical methodologies, including optimal input-output adjustments, to move towards the efficiency frontier. For instance, DMU4's low performance across multiple perspectives highlights targeted interventions, while DMUs such as DMU1 and DMU10 demonstrate consistent optimal performance, offering a benchmark for others.

5.3 | Suggestions for Future Research

I. Exploring the proposed framework in uncertain or incomplete data environments to address performance evaluation in real-world conditions where precise data may not be available.

II. Comparing the DNSBM-DEA with alternative DEA models to identify more effective methodologies for measuring municipal performance.

III. Proposing a BSC-based model that incorporates municipal social responsibility and evaluates its impact on overall performance, especially in the customer and community-oriented perspectives.

IV. Introducing DEA models that directly account for inefficiencies related to intermediate and intertemporal products, which can provide a more nuanced understanding of long-term efficiency trends.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

All data are included in the text.

Funding

This research received no specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Reference

[1] Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European journal of operational research*, *2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

[2] Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management science*, *30*(9), 1078–1092. https://doi.org/10.1287/mnsc.30.9.1078

[3] Cook, W. D., Seiford, L. M., & Zhu, J. (2004). Models for performance benchmarking: measuring the effect of e-business activities on banking performance. *Omega*, *32*(4), 313–322. DOI:10.1016/j.omega.2004.01.001

[4] Nojehdehi, R. R., Valami, H., & Najafi, S. E. (2011). Evaluating the membership degree of the DMU's related to the fuzzy frontier in DEA with fuzzy input-output levels: A geometrical approach. *Trends in advanced science and engineering. tase*, *4*, 7–15.

[5] Nojehdehi, R. R., Abianeh, P. M. M., & Valami, H. B. (2012). A geometrical approach for fuzzy production possibility set in data envelopment analysis (DEA) with fuzzy input-output levels. *African journal of business management*, *6*(7), 2738. DOI:10.5897/AJBM11.2614

[6] Rasinojehdehi, R., & Valami, H. B. (2023). a Comprehensive neutrosophic model for evaluating the efficiency of airlines based on SBM model of network Dea. *Decision making: applications in management and engineering*, *6*(2), 880–906. DOI:10.31181/dma622023729

[7] Rasi Nojehdehi, R., Bagherzadeh Valami, H., & Najafi, S. E. (2023). Classifications of linking activities based on their inefficiencies in Network DEA. *International journal of research in industrial engineering*, *12*(2), 165–176. https://doi.org/10.22105/riej.2022.360989.1335

[8] Bagherzadeh Valami, H., & Raeinojehdehi, R. (2016). Ranking units in data envelopment analysis with fuzzy data. *Journal of intelligent & fuzzy systems*, *30*, 2505–2516. DOI:10.3233/IFS-151756

[9] Abyaneh, P. M., Nojehdehi, R. R., & Alem, A. (2012). Quality function deployment in engineering, procurement and construction projects. *Journal of basic and applied scientific research*, *2*(4), 4167–4173.

[10] Avkiran, N. K., & McCrystal, A. (2012). Sensitivity analysis of network DEA: NSBM versus NRAM. *Applied mathematics and computation*, *218*(22), 11226–11239. DOI:10.1016/j.amc.2012.05.014

[11] Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European journal of operational research*, *130*(3), 498–509. https://doi.org/10.1016/S0377-2217(99)00407-5

[12] Namakin, A., Najafi, S. E., Fallah, M., & Javadi, M. (2018). A new evaluation for solving the fully fuzzy data envelopment analysis with z-numbers. *Symmetry*, *10*(9), 384.

[13] Akbarian, M., Najafi, E., Tavakkoli-Moghaddam, R., & Hosseinzadeh-Lotfi, F. (2015). A network-based data envelope analysis model in a dynamic balanced score card. *Mathematical problems in engineering*, *2015*(1), 914108.

[14] Färe, R., & Grosskopf, S. (1996). Productivity and intermediate products: A frontier approach. *Economics letters*, *50*(1), 65–70. https://doi.org/10.1016/0165-1765(95)00729-6

[15] Tone, K., & Tsutsui, M. (2009). Network DEA: A slacks-based measure approach. *European journal of operational research*, *197*(1), 243–252.

[16] Tone, K., & Tsutsui, M. (2014). Dynamic DEA with network structure: A slacks-based measure approach. *Omega*, *42*(1), 124–131.

[17] Huang, Y., & Wang, M. (2024). Efficiency evaluation of China's high-tech industry with a dynamic network data envelopment analysis game cross-efficiency model. *Operational research*, *24*(1), 8.

[18] Liu, M., Zhang, C., Huang, W., Wang, M., & Xiao, G. (2024). A dynamic network data envelopment analysis cross-efficiency evaluation on the benefits of bus transit services in 33 Chinese cities. *Transportation letters*, *16*(4), 392–404. https://doi.org/10.1080/19427867.2023.2198109

[19] Anouze, A. L., Al Khalifa, M. M., & Al-Jayyousi, O. R. (2024). Reevaluating national innovation systems: An index based on dynamic-network data envelopment analysis. *Socio-economic planning sciences*, *95*, 102003. https://doi.org/10.1016/j.seps.2024.102003

[20] Kaplan, R. S., & Norton, D. P. (2004). The strategy map: guide to aligning intangible assets. *Strategy & leadership*, *32*(5), 10–17.

[21] Jaberi Hafshjani, M., Najafi, S. E., Hosseinzadeh Lotfi, F., & Hajimolana, S. M. (2021). [Retracted] A Hybrid BSC-DEA Model with Indeterminate Information. *Journal of mathematics*, *2021*(1), 8867135.

[22] Elbanna, S., Kamel, H., Fatima, T., & Eid, R. (2022). An investigation of the causality links in the balanced scorecard: The case of the Gulf Cooperation Council hospitality industry. *Tourism management perspectives*, *41*, 100934. DOI:10.1016/j.tmp.2021.100934

[23] Amer, F., Hammoud, S., Khatatbeh, H., Lohner, S., Boncz, I., & Endrei, D. (2022). The deployment of balanced scorecard in health care organizations: is it beneficial? A systematic review. *BMC health services research*, *22*, 1–14.

[24] Chaharlang, Y., Soleimani, H., Mehdizadeh, E., & Alinezhad, A. (2023). Introduction of an Integrated System for Measuring the BSC and DEA-Based Performance of Social Systems Using Uncontrollable Factors: A Case Study of Shahriar Municipalities. *Buildings*, *13*(1), 242.

[25] Najafi, E., Aryanezhad, M., & others. (2011). A BSC-DEA approach to measure the relative efficiency of service industry: a case study of banking sector. *International journal of industrial engineering computations*, *2*(2), 273–282.

[26] Lu, M.-T., Hsu, C.-C., Liou, J. J. H., & Lo, H.-W. (2018). A hybrid MCDM and sustainability-balanced scorecard model to establish sustainable performance evaluation for international airports. *Journal of air transport management*, *71*, 9–19.

[27] Daraio, C., Di Leo, S., Iazzolino, G., & Laise, D. (2023). DEA, balanced scorecard and intellectual capital including the gender dimension: A comprehensive list of indicators. *International transactions in operational research*, *30*(6), 2972–3012.

[28] Hristov, I., Cristofaro, M., Camilli, R., & Leoni, L. (2024). A system dynamics approach to the balanced scorecard: a review and dynamic strategy map for operations management. *Journal of manufacturing technology management*, *35*(4), 705–743.